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Metal Returns, Stock Returns and Stock Market Volatility*

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ABSTRACT

Given the extensive participation of mining stocks in the Peruvian stock market, the Lima Stock Exchange (BVL) provides an ideal setting for exploring both the impact of metal returns on mining stock returns and stock market volatility, and the comovements between mining stock returns and metal returns. This research is a first attempt to explore these issues using international metal prices and the prices of the most important mining stocks on the BVL and the IGBVL index. To achieve this, we use univariate GARCH models to model individual volatilities, and the Exponentially Weighted Moving Average (EWMA) method and multivariate GARCH models with time-varying correlations to model comovements in returns. We found that Peruvian mining stock volatilities mimic the behavior of metal volatilities and that there are important correlation levels between metals and mining stock returns. In addition, we found time-varying correlations with distinctive behavior in different periods, with rises potentially related to international and local historical events.

Keywords: Comovements, Peruvian stock market.

JEL classification: C22, C58, G15.

Retornos metálicos, rendimiento de las acciones y volatilidad del mercado de valores

RESUMEN

Dada la amplia participación de acciones mineras en el mercado de valores peruano, la Bolsa de Valores de Lima (BVL) resulta un escenario ideal para explorar tanto el impacto de los rendimientos de acciones de metales en los rendimientos de las acciones mineras y la volatilidad del Mercado de valores, así como los co-movimientos entre los rendimientos de las acciones mineras y los rendimientos de los metales. Este estudio es un primer intento en explorar estos temas usando precios internacionales de los metales y los precios de las acciones mineras más

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importantes de la BVL y del índice IGBVL. Para conseguir esto, hemos usado modelos GARCH univariados para modelar las volatilidades individuales, y el método de Media Móvil Ponderada Exponencialmente (EWMA) y modelos GARCH multivariados con correlaciones de variantes en el tiempo a modelos de co-movimientos en rendimientos. Hemos encontrado que las volatilidades imitan el comportamiento de las volatilidades de los metales y que hay importantes niveles de correlación entre los metales y el retorno de las acciones mineras. Adicionalmente, encontramos correlaciones variantes en el tiempo con un comportamiento distintivo en periodos diferentes, el que aumenta potencialmente en relación con eventos históricos internacionales o nacionales.

Palabras clave: co-movimientos, mercado de valores peruano.

Clasificación JEL: C22, C58, G15.

1. INTRODUCTION

The economic boom experienced by the Peruvian economy have often been associated with external factors such as favorable international commodity prices, including the prices of gold, copper, silver and zinc, among other metals. In consequence, mining companies are highly important actors in the economy. This importance is reflected in the Peruvian stock market, where mining stock constitutes the largest sector due to its strong participation in terms of size and traded volume. Given this fact and despite a recent increase in diversification, the Peruvian stock market has been historically considered as a *mining stock market*.

This importance is also reflected in the main index of the BVL: the *Índice Selectivo de la Bolsa de Valores de Lima* (IGBVL). This is a market-value-weighted index with a base date of December 30, 1991 and a base value of 100, and is commonly regarded as the benchmark of the Peruvian stock market. As at December 2014, the IGBVL was comprised of 27 stocks accounting for 82% of total market operations and 84% of the total volume traded. At least twice a year the BVL revaluates the companies listed on the index based on volume and number of operations, in order to consider the most representative stocks of the market. Mining companies' participation in the index averaged 42% of the accumulated weight and 34% of the total number of stocks over the last decade. Despite recent diversification the values are still high, standing at 34% and 30% respectively as at December 2014.

The high participation of the mining sector at both market and index level is of particular interest, as it means higher market exposure to shocks as one of the factors that affect the performance of mining stocks. This renders the BVL an ideal setting for studying the comovements of mining stocks and the market index with metal prices. In this paper, a sample of selected mining companies, metals and the IGBVL for the period January 2, 2004 to December 19, 2014 is studied. We chose this particular period because it corresponds to a boom in metal prices and a series of volatile local and international events.

In this paper we focus on modeling comovements between metal price returns and the BVL's mining stocks, as well as the IGBVL index. For this purpose we selected three of the most representative mining companies in terms of metal diversification, and which are also important in terms of market capitalization, frequency and number of BVL transactions: Volcan Cia Minera SAA (Volcan), Southern Copper Corporation (Southern) and Cia de Minas Buenaventura SA (Buenaventura). For instance, as at December of 2014, Volcan ranked #2 in terms of operations (8.83% of total market operations), Southern ranked #1 in terms of market capitalization (20.73% of total market capitalization), and Buenaventura ranked #1 in terms of frequency (100% of trading days). As to the most-exploited metals, Volcan produce zinc, lead and silver; Southern produce cooper zinc and silver; and Buenaventura produce gold, silver, lead and zinc. Therefore, in this paper we selected gold, copper, silver, zinc, and lead as the metals. According to the United States Geological Survey (USGS) Minerals Resources Program, Peru ranks 6th in gold, 4th in lead, 2nd in cooper, 2nd in zinc, and 1st in silver for worldwide mine production by country, which confirms the representativeness of the mining companies and metals chosen[1].

Even though the study of metal volatility and comovements has become an active area of research in recent years - see for example Ng and Craig (1994), Brunetti and Gilbert (1995), Batten et al. (2008), Hammoudeh and Yuan (2008), Hammoudeh et al. (2009) and Mei-hsiu (2010) - the study of the relationship between metal volatility and stock market volatility is scarce, see for instance Morales (2008) and Mishra et al. (2010). Moreover, as far as we know there is no academic literature that studies the effects of metal returns and volatilities on the principal mining stocks in the Peruvian stock market, or on its main stock market index, the IGBVL. This study is an attempt to help fill this gap in the literature

In addition, the findings of this paper constitute valuable inputs for portfolio risk management. The recent trend of capital market integration has once again renewed interest and focused attention on the structure of correlations and the benefits of portfolio diversification. As first described by Markowitz's modern portfolio theory, the degree to which investors can reduce risk by diversifying their portfolio depends on the correlation between assets. Because correlation between assets gives us an idea as to how two assets move in relation to each other, the lower the correlation between them, the greater the potential for reducing risk. Every day Peruvian portfolio managers build and optimize their portfolios using mining stocks due to the importance of this sector to the economy. Therefore, measuring the movements and comovements of these two types of assets is a key component of their risk and optimization strategies.

Based on weekly returns of selected mining stocks, the IGBVL index, and some metals, the main contributions of this paper are twofold.

[1] Source:http://www.indexmundi.com/minerals. Accessed on May, 2012.

First, the volatility of the selected time series is modeled. This is done through univariate GARCH models which are a typical choice for modeling volatility in metal returns, see for example Watkins and McAleer (2008). In recent literature, Zevallos (2008) uses univariate GARCH models to model volatility in the Peruvian stock market.

The second contribution of this paper is to model the comovements between mining stock returns and IGBVL index with metal returns. Thus, for each of the selected mining companies, we choose the primary metals produced and estimate the conditional correlation. Specifically, we consider the following cases: Southern, copper; Buenaventura, with a basket of Gold and Silver; (referred to as Gold-Silver); Volcan, with a basket of Lead and Zinc (named Lead-Zinc); Volcan, with Silver; IGBVL, with Gold-Silver; and IGBVL, with Copper.[2] In addition, to gain insight into the relationship between the selected Peruvian mining stocks, we consider the following cases: Buenaventura with Southern; Buenaventura with Volcan; and Southern and Volcan. These comovements are estimated using the Exponentially Weighted Moving Average estimator and multivariate GARCH models with time-varying correlations: the Dynamic Conditional Correlation and Integrated Dynamic Conditional Correlation models (Engle, 2002) and the Asymmetric Dynamic Conditional Correlation model (Capiello et al., 2006). These methods are convenient choices in estimating conditional correlation dynamics because of their simplicity and parsimony.

The remainder of this paper is organized as follows. Section 2 briefly expounds the methodology used in this study, the data and empirical findings are presented in Section 3, and final conclusions are given in Section 4.

2. METHODOLOGY

In this section we describe the methodology used to estimate the volatilities and the time-varying conditional correlations (linkages) between the time series returns considered. This approach follows Filleti et al. (2008).

Consider a multivariate time series of returns $r_t = (r_{1,t}, \ldots, r_{K,t})^T$, $t = 1, \ldots, n$ and assume that

$$r_t = \mu_t + H_t^{1/2}\,\varepsilon_t, \tag{1}$$

where $\{\varepsilon_t\}$ is a sequence of independent and identically distributed vectors of dimension $K \times 1$ with zero mean and covariance matrix and equals the identity, μ_t is a $K \times 1$ vector, and H_t is a $K \times K$ matrix. In addition, ε_t is independent of the past values of μ_t and H_t,

[2] Hereinafter, we use capital letters to refer to metals

and both μ_t and H_t are constants conditioned on $\mathcal{F}_{t-1}$, the information available up to time $(t-1)$. Then $E(r_t|\mathcal{F}_{t-1}) = \mu_t$ and $Var(r_t|\mathcal{F}_{t-1}) = H_t$ are the conditional mean and conditional covariance matrix of r_t, respectively. The elements of H_t are denoted by: $h_{i,t}$ for the conditional variances of the i-th return and $h_{ij,t}$ for the conditional covariance of i-th and j-th returns. Therefore, the correlation between the i-th and j-th time series at time t conditioned on the past is

$$\rho_{ij,t} = \frac{h_{ij,t}}{\sqrt{h_{i,t}h_{j,t}}}, \quad i, j = 1, \ldots, K. \tag{2}$$

Next, we present two methods for estimating the conditional correlations $\rho_{ij,t}$.

2.1. Exponentially Weighted Moving Average

The Exponential Weighted Moving Average (EWMA) method is usually employed by practitioners because its simplicity and the estimated correlations obtained using this method are frequently used as benchmarks to be compared against parametric model estimations. The basic idea of the EWMA method is that the elements of H_t evolve randomly in a way that depends on a smoothing parameter λ. Specifically, the method assumes that estimates of H_t are calculated as

$$\hat{H}_t = \lambda \hat{H}_{t-1} + (1-\lambda)(r_{t-1} - \hat{\mu}_{t-1})^T (r_{t-1} - \hat{\mu}_{t-1}), \quad t = 2, \ldots, n. \tag{3}$$

Thus, $\hat{H}_t$ is a weighted mean where λ controls the degree of smoothing. In the literature the smoothing parameter λ can be chosen in an *ad hoc* way as a value in the interval (0.94,0.97) according to the specific characteristics of the time series returns, or can be estimated by: assuming that the returns follow a normal multivariate distribution (see section 13.2 in Zivot and Wang (2005)) or by minimizing the mean squared error of prediction assuming benchmarks values for the elements of H_t. Since the EWMA method is employed in this paper by way of explanation, we prefer to use the *ad hoc* value $\lambda = 0.94$ instead of estimating it. We thereby avoid assuming a distribution for returns and the use of controversial benchmark values for H_t. In addition, the initial conditional covariance $\hat{H}_1$ can be estimated by the sample covariance using all data or a subset thereof. In this paper we estimate $\hat{H}_1$ as the sample covariance of the first 20 observations.

Having estimated the elements of H_t, we estimated the conditional correlations using the plug-in estimate of (2), i.e. $\hat{\rho}_{ij,t} = \hat{h}_{ij,t}/(\hat{h}_{i,t}\hat{h}_{j,t})^{1/2}$, $i, j = 1, \ldots, K$.

2.2. Multivariate GARCH Models

In the literature several multivariate GARCH models have been proposed: the Constant Conditional Correlation model of Bollerslev (1990), the BEKK model proposed in Engle and Kroner (1995), the OGARCH model of Alexander (2001a,b), the Dynamic Conditional Correlation (DCC) and Integrated Dynamic Conditional Correlation (IDCC) models proposed by Engle (2002), the GO-GARCH model of van der Weide (2002), and the scalar Asymmetric Dynamic Conditional Correlation (A-DCC) model of Cappiello et al. (2006), among others.

As discussed by Caporin and McAleer (2014), two of the most studied topics in multivariate GARCH models are the *curse of dimensionality* and *feasible model estimation*. Both are related to the specification of H_t; the course of dimensionality has to do with the number of parameters needed to define the conditional variances and conditional correlations. As expected, in the face of a high dimensional problem, the quality of the estimation is affected. This occurs especially when we have to estimate a multivariate model for several small-sized time series.

In this paper, we seek to estimate multivariate models for small-sized time series. To do so, we used the Dynamic Conditional Correlation (DCC) and Integrated Dynamic Conditional Correlation (IDCC) models proposed by Engle (2002) and the scalar Asymmetric Dynamic Conditional Correlation (ADCC) model of Cappiello et al. (2006). The main advantage of these models (referred to hereinafter as DCC-type models) compared to several other multivariate GARCH models lies in their parsimony in explaining the time varying correlation. For this reason, we choose these models for estimating the correlation dynamics of the mining stocks, IGBVL index and metal returns.

One of the main features of DCC-type models is that they allow for two-stage estimation of the conditional covariance matrix H_t. Thus, in the first stage, univariate volatility models are fitted for each of the assets, and estimates of $h_{i,t}$ are obtained for $i = 1, ..., K$; in the second stage, parameter estimates of the conditional correlation are obtained based on the asset returns transformed by their estimated standard deviations resulting from the first stage. The properties of the two-step estimators have been obtained by Engle and Sheppard (2001). The estimation can be also done in one step by maximizing the full likelihood; however, the two-step procedure enables mitigation of the problem of finding the minima in a highly dimensional and nonlinear optimization problem. We follow the usual path of estimating the model in two steps.

We model the volatility of the univariate time series returns, $h_{i,t}$, by means of ARCH models (Engle, 1982) or GARCH models (Bollerslev, 1986). GARCH models are a typical choice for modeling volatility in metal returns, see for example Watkins and McAleer (2008). For instance, let $r_{k,1}$, ..., $r_{k,n}$ be returns of the k-th time series and assume that these observations were generated by the model,

$$r_{k,t} = \mu + \pi(B)\varepsilon_{k,t}, \tag{4}$$

$$\varepsilon_{k,t} = \sqrt{h_{k,t}}\varepsilon_{k,t}, \tag{5}$$

where for fixed k $\{\varepsilon_{k,t}\}$ is a sequence of independent identically distributed random variables with mean zero and variance one. The filter $\pi(B)$, where B is the backshift operator, accounts for correlation in the levels. Usually, financial returns are uncorrelated, then $\pi(B) = 1$, but in some cases a serial correlation is presented. In this paper, we find it convenient to filter some time series using the MA(1) filter $\pi(B) = (1 + \theta B)$ or the ARFIMA(0,d,1) filter $\pi(B) = (1 - B)^{-d}(1 + \theta B)$. In addition, we assume that the *volatility*[3] of the k-th time series, $h_{k,t}$, evolves as an ARCH(p) model,

$$h_{k,t} = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{k,t-i}^2, \tag{6}$$

or as a GARCH(1,1) model,

$$h_{k,t} = \omega + \alpha\varepsilon_{k,t-1}^2 + \beta h_{k,t-1}. \tag{7}$$

To reproduce heavy tails which are usually observed in financial time series returns, we assume that $\varepsilon_{t,k}$ follows a Generalized Exponential Distribution (GED) with parameter v. This family includes the Gaussian distribution when $v = 2$ and smaller values of this parameter indicate heavy tails.

In models (6) and (7), the present volatility depends on previous shocks (related to α and α_i) and previous volatility (related to β). For GARCH models, values of $\alpha + \beta$ near to 1 indicates high persistence in volatility.

Once the univariate volatility models are specified, we have to specify the dynamics between the K considered time series, i.e., the model for the conditional correlation between assets i and j at time t, denoted by $\rho_{ij,t}$. In DCC, IDCC and ADCC models, H_t is decomposed as

$$H_t = D_t R_t D_t, \tag{8}$$

where D_t is a $K \times K$ diagonal matrix with nonzero elements $\sqrt{h_{i,t}}$, $i = 1, \ldots, K$, i.e., $D_t = diag\left\{\sqrt{h_{1,t}}, \ldots, \sqrt{h_{K,t}}\right\}$ and R_t is the correlation matrix conditional on $\mathcal{F}_{t-1}$ with elements given by (2).

Defining the standardized vector

$$\varepsilon_t = D_t^{-1}(r_t - \mu_t). \tag{9}$$

In DCC models, conditional correlations are calculated by

$$\rho_{ij,t} = \frac{\delta_{ij,t}}{\sqrt{\delta_{ii,t}\delta_{jj,t}}} \qquad i, j = 1, \ldots, K, \tag{10}$$

[3] In the literature $h_{k,t}$ or $\sqrt{h_{k,t}}$ are refered as volatility.

where $\delta_{ij,t}$ are elements of matrix Δ_t, which evolves by following

$$\Delta_t = S(1 - a - b) + a\varepsilon_{t-1}\varepsilon_{t-1}^T + b\Delta_{t-1} \tag{11}$$

and S is the unconditional correlation matrix of ε_t, $E[\varepsilon_t\, \varepsilon_t^T]$. Note that once the standardized vectors ε_t's and S are determined, we need only two parameters (a and b) to calculate *all* the conditional correlations. In (11) the necessary and sufficient condition for second order stationarity is $a + b < 1$. However, when $a + b = 1$ we still obtain a strict stationary model. This version, defined as

$$\Delta_t = (1 - \lambda)\varepsilon_{t-1}\varepsilon_{t-1}^T + \lambda\Delta_{t-1} \tag{12}$$

is called a Integrated Dynamic Conditional Correlation (IDCC) model.

Models (11) and (12) do not allow for asset-specific news or asymetries. To incorporate these features, Cappiello et al. (2006) propose the ADCC model with

$$\Delta_t = S\left(1-a-b\right) - gS^{å} + a\varepsilon_{t-1}\varepsilon_{t-1}^{\mathrm{T}} + g\eta_{t-1}\eta_{t-1}^{\mathrm{T}} + b\Delta_{t-1}, \tag{13}$$

where $S^{å} = E[\eta_t\eta_t^T]$, $\eta_t = I_{[\varepsilon_t<0]} \circ \varepsilon_t$, with "o" being the Hadamard product and $I_{[.]}$ a $K \times 1$ indicator function which takes on value one if the argument is true and zero otherwise. A necessary and sufficient condition to ensure that the conditional covariance matrix is positive definite is $a + b + \delta g < 1$, where δ is the maximum eigenvalue of $S^{-1/2}S^{å}S^{-1/2}$. In applications, S and $S^{å}$ are estimated using moment estimators $n^{-1}\sum_{t=1}^{n}\varepsilon_t\varepsilon_t^T$ and $n^{-1}\sum_{t=1}^{n}\eta_t\eta_t^T$, respectively.

Next we describe the estimation procedure of DCC-type models. Assuming that ε_t follows a multivariate normal distribution, then $r_t \mid \mathcal{F}_{t-1} \sim N(\mu_t, H_t)$. Therefore the conditional log-likelihood at time t is,

$$l_t = -\frac{K}{2}\log\left(2\pi\right) - \frac{1}{2}\log\left|H_t\right| - \frac{1}{2}(r_t - \mu_t)^{\mathrm{T}} H_t^{-1}\left(r_t - \mu_t\right), \tag{14}$$

and substituing (8) and (9) in (14), we obtain

$$l_t = -\frac{K}{2}\log\left(2\pi\right) - \log\left|D_t\right| - \frac{1}{2}\log\left|R_t\right| - \frac{1}{2}\varepsilon_t^{\mathrm{T}} R_t^{-1}\varepsilon_t. \tag{15}$$

Parameters are estimated by maximum likelihood in two steps. In the first step the univariate volatility models are estimated, i.e., we obtain $\hat{\mu}_{i,t}$ and $\hat{h}_{i,t}$ for $i = 1, ..., K$ and $t = 1, ..., n$. In the second step, we estimate the standardized vector ε_t (9) by $\hat{\varepsilon}_t = \hat{D}_t^{-1}(r_t - \hat{\mu}_t)$ for $t = 1, ..., n$. Then, the parameters (θ) responsible for the dynamics of the correlations (in R_t or equivalently in Δ_t) are obtained by maximizing

$$l\left(\theta\right) = -\frac{1}{2}\sum_t \log\left|R_t(\theta)\right| - \frac{1}{2}\sum_t \hat{\varepsilon}_t^T R_t(\theta)^{-1}\,\hat{\varepsilon}_t. \tag{16}$$

The maximization is carried out using numerical routines. In this paper we implemented the Nelder and Mead (1965) optimization algorithm in an *R* program. For DCC models, sufficient conditions for the consistency and asymptotic normality of the estimators are based on Newey and McFadden (1994) results, see Engle and Sheppard (2001).

On the other hand, to assess if the estimated model captures the dependence structure, we use two diagnostics procedures. First, we evaluated whether the univariate standardized residuals $\{\hat{\varepsilon}_{i,1}, \ldots, \hat{\varepsilon}_{i,n}\}$ and its squares present correlation structure using the Weighted Ljung-Box statistics of Fisher and Gallagher (2012). Second, to assess whether there is any remaining cross-correlation, we use the multivariate white noise test of Hosking(1980) on the multivariate residuals

$$z_t = \hat{R}_t^{-1/2}\,\hat{\varepsilon}_i. \tag{17}$$

and its squares.

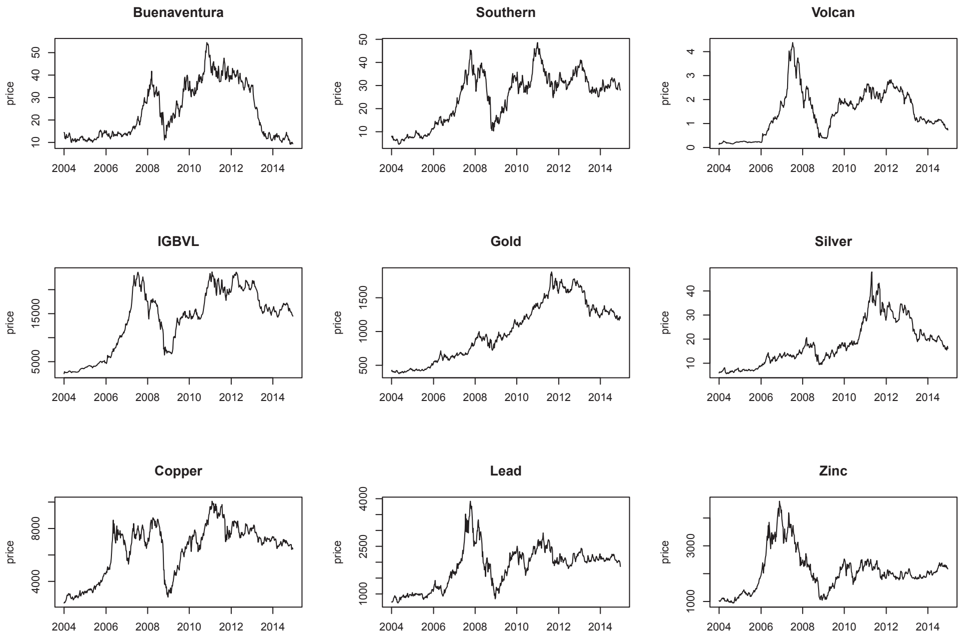
3. EMPIRICAL FINDINGS

In this section, we apply the methodology described in the previous section to the time series returns of Peruvian mining stocks, the IGBVL index, and metals. First we present the data and then we discuss the findings. Calculations are performed using the *R* package; for univariate modeling we use the *rugarch* package of Ghalanos (2014), and we write a program for the multivariate fits.

3.1. Data Description

Weekly closing prices are gathered for the stocks of three Peruvian mining companies (Buenaventura (BVN), Southern (SCCO), and Volcan (VOLCABC1)); for the IGBVL index; and for gold, copper, silver, zinc, and lead. The sample covers the period from January 2, 2004 to December 19, 2014. The data is obtained from the Bloomberg Professional database, which uses the London Metal Exchange (LME) as a source for metal prices. We work with weekly prices instead of daily prices to mitigate the lack of synchronicity between the BVL and the LME, and to overcome the missing data due to different holiday dates for international metal markets and BVL. Specifically, we used the Friday closing prices.

Figure 1. Prices



In Figure 1 we show the time series for stock prices, the index, and metals. Here it can be seen that all stocks and the IGBVL index increased markedly towards the middle of 2007 and the beginning of 2008, and then fell rapidly after the Lehman Brothers crisis in 2008. This pattern also applies to all metal prices, except for Silver and Gold which tend to act as safe-haven assets at times of crisis. For these two metals, a near-constant upward trend can be seen, with a slight fall around the time of the Lehman Brothers bankruptcy. After this period, the prices increased up to historical maximums in 2011, and then decreased again. Interestingly, since the beginning of 2012, Buenaventura's and Volcan's prices have been falling, by the end of 2014 reaching similar (low) values to those recorded during the Lehman Brothers bankruptcy period. In addition, Southern and IGBVL prices also exhibit very similar behavior when comparing zinc with lead, and gold with silver.

Weekly returns were calculated as the difference in Friday log-prices, in percentage, resulting in 572 observations for each time series. In Table 1 we report some descriptive statistics for weekly returns. Mean returns are large for IGBVL[4] and all stocks except for Buenaventura, when compared in relative terms to metal returns. The standard deviation is roughly the same for all stocks and much bigger than the corresponding value for the

[4] Previous studies about the stylized facts of IGBVL returns have been conducted by Zevallos (2008) using daily data, and by Humala and Rodriguez (2013) using daily, weekly and monthly data.

IGBVL index. Skewness values are negative except for Buenaventura and Volcan, and IGBVL and Volcan have higher kurtosis than the remaining stocks and metals. Overall, skewness and kurtosis values evidence asymmetric unconditional distributions with heavy tails.

Table 1. Descriptive statistics of returns

	Mean	Std Dev	Skewness	Kurtosis	Min	Max
Buenaventura	-0.075	6.312	0.00	6.47	-28.77	38.87
Southern	0.219	6.485	-0.37	6.37	-34.42	28.84
Volcan	0.302	7.433	0.50	14.45	-51.08	56.39
IGBVL	0.307	3.963	-1.07	16.02	-34.60	19.31
Gold	0.185	2.685	-0.43	4.41	-9.77	12.64
Silver	0.173	4.872	-1.18	7.60	-29.59	14.24
Copper	0.176	4.188	-0.91	7.54	-25.20	13.52
Lead	0.159	5.515	-0.19	4.77	-18.78	23.98
Zinc	0.131	4.786	-0.26	4.08	-17.99	15.95
Gold-Silver	0.179	3.593	-0.91	5.69	-17.80	13.44
Lead-Zinc	0.145	4.662	-0.31	4.01	-15.60	19.00

Figure 2. Returns

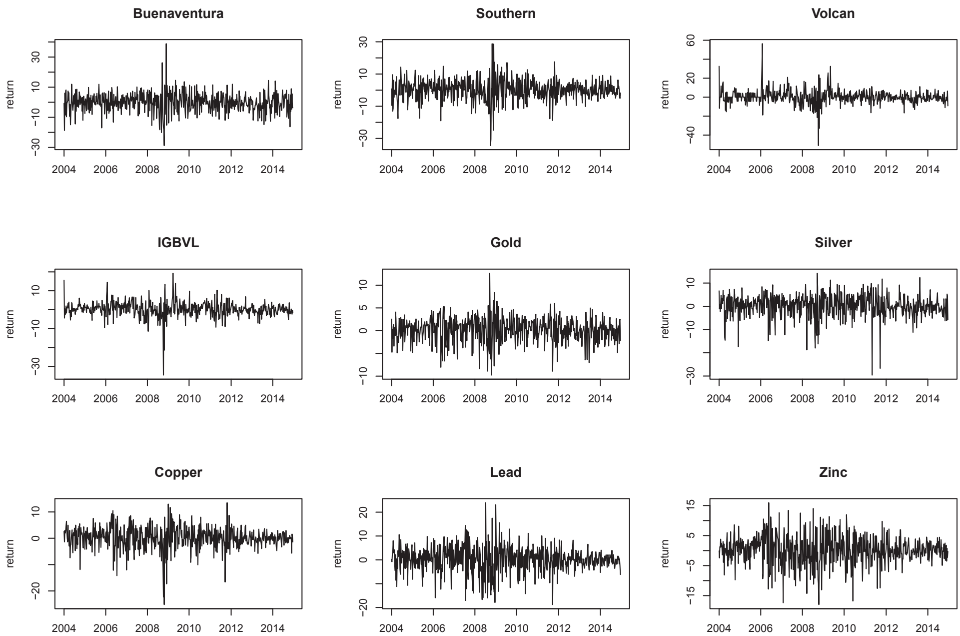


Figure 2 shows the time series returns for mining stocks, IGBVL index, and metals. These graphs show that mining stocks and IGBVL have undergone periods of high volatility in the subprime crisis and the period following the Lehman Brothers bankruptcy. Nevertheless, another source of volatility for Peruvian stock market returns could be associated with political expectations around elections, see for example Zevallos (2008) and Rodriguez and Vargas (2012). In 2006, the electoral period seems to have affected Southern, Volcan, IGBVL and, to a lesser extent, Buenventura, while in 2011 it seems to have affected IGBVL and Southern, and, to a lesser extent, Volcan. In the case of metal prices, high volatility can be observed around the times of the subprime crisis and the Lehman Brothers bankruptcy. In the case of gold, silver, copper and zinc, we also observe periods of high volatility in mid-2006 and mid-2011.

Table 2 shows the Pearson correlations between each pair of time series returns. It can be observed that each mining company is highly correlated with the metals that it primarily produces. For instance, Buenaventura, with Gold and Silver; Southern, with Copper; and Volcan, with Zinc and Lead. Among the mining companies, Buenaventura is more closely correlated with Southern than with Volcan. In addition, IGBVL and Volcan returns have an impressive correlation of 0.84.

Table 2. Unconditional correlations

	Southern	Volcan	IGBVL	Gold	Silver	Copper	Lead	Zinc	Gold-Silver	Lead-Zinc
Buenaventura	0.50	0.29	0.44	0.61	0.56	0.34	0.23	0.26	0.61	0.27
Southern		0.45	0.59	0.31	0.45	0.61	0.46	0.48	0.42	0.52
Volcan			0.84	0.15	0.24	0.44	0.35	0.36	0.22	0.39
IGBVL				0.26	0.36	0.53	0.38	0.41	0.34	0.43
Gold					0.79	0.34	0.25	0.31	0.91	0.31
Silver						0.45	0.34	0.42	0.97	0.42
Copper							0.64	0.71	0.43	0.74
Lead								0.64	0.33	0.92
Zinc									0.40	0.89
Gold-Silver										0.40

Given that Gold and Silver prices evolve in a similar way, and their returns are highly correlated, we consider it pertinent to build a two-asset basket, Gold-Silver, with equal weights for both metals. In the same way and for the same reasons, we create a basket known as Lead-Zinc. In Tables 1 and 2, we have included, respectively, the descriptive statistics of the basket's time series and the correlations among the time series considered. In Table 2 in particular, it can be observed that Buenaventura's correlation with Gold-Silver is higher than the correlation with each individual metal. We find the same result when we compare the correlation between Volcan and Lead-Zinc vs. the correlations with each individual metal. Hereinafter, we center our attention on the Gold-Silver and Lead-Zinc baskets rather than the individual Gold, Silver, Lead and Zinc time series.

3.2. Estimation of Volatilities and Linkages

For each time series several univariate ARCH-type models with GED errors were fitted. In Table 3 we present the parameter estimates of the best univariate volatility fits (among ARCH, GARCH, EGARCH and TGARCH specifications) in terms of significance of coefficients, diagnostics or information criteria. In all cases, the coefficient μ in (4) was estimated by the respective mean shown in Table 1. However, for some time series we need to filter the data to account for serial correlation in the levels. For instance, we fitted an ARMA(1,1) model for Volcan with estimates $\hat{\phi}=0.933(0.041)$, $\hat{\theta}=-0.878(0.053)$ and an ARFIMA(0,d,1) model for IGBVL with estimates $\hat{\theta}=-0.058(0.051)$, $\hat{d}=0.188(0.045)$, where the standard errors are given in parenthesis. Thus, these parameter level estimates are highly significant, excepting the estimate for θ in the IGBVL fit.

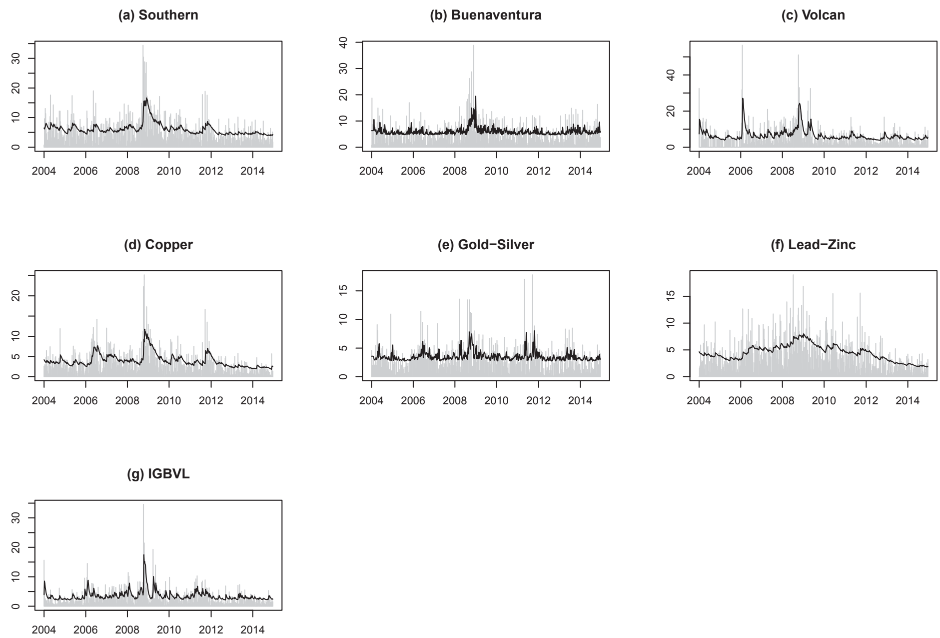
Table 3. Univariate volatility parameter estimates

	Buenaventura	Southern	Volcan	IGBVL	Gold-Silver	Copper	Lead-Zinc
Model	ARCH(5)	GARCH(1,1)	GARCH(1,1)	GARCH(1,1)	ARCH(5)	GARCH(1,1)	GARCH(1,1)
ω	21.2132	1.2233	3.4740	1.4950	7.2950	0.2899	0.0068
	(3.1231)	(0.7847)	(2.0390)	(0.7777)	(1.2346)	(0.2155)	(0.0569)
α_1	0.0434	0.0928	0.1913	0.2631	0.0806	0.1143	0.0498
	(0.0391)	(0.0284)	(0.0662)	(0.0996)	(0.0588)	(0.0328)	(0.0135)
α_2	0.1083				0		
	(0.0518)				(0.0836)		
α_3	0.0000				0.0312		
	(0.0549)				(0.0555)		
α_4	0.0305				0.1692		
	(0.0453)				(0.0829)		
α_5	0.2299				0.1688		
	(0.0660)				(0.0701)		
β_1		0.8748	0.7377	0.6427		0.8728	0.9492
		(0.0405)	(0.0931)	(0.1269)		(0.0376)	(0.0136)
v	1.54	1.55	1.14	1.19	1.45	1.42	1.84
	(0.13)	(0.13)	(0.09)	(0.09)	(0.11)	(0.11)	(0.16)
$BL[m]$	0.82[2]	0.62[2]	0.28[2]	0.48[2]	0.73[2]	0.35[2]	0.57[2]
	0.78[2]	0.41[5]	0.52[5]	0.79[5]	0.73[5]	0.46[5]	0.73[5]
$BL2[m]$	0.52[14]	0.65[5]	0.15[5]	0.95[5]	0.47[14]	0.78[5]	0.58[5]
	0.49[24]	0.28[9]	0.36[9]	0.98[9]	0.37[24]	0.39[9]	0.42[9]

[a] [a] BL[m] and BL2[m] are the p-values of Fisher and Gallagher's (2012) Weighted Ljung-Box statistic with m lags for standardized and squared residuals, respectively. Standard errors in parenthesis.

In Table 3 we observe that coefficients ν are highly significant, as are the estimates of α and β in the GARCH fits, and ω estimates are significant at 10% or less using one-sided alternative hypothesis, except for the Lead-Zinc case. Additionally, some of the α_i estimates in ARCH fits are not significant. In all GARCH(1,1) estimations we find volatility with high persistence, and the estimated values of ν show that the distribution of the shocks has heavy tails. The p-values of Fisher and Gallagher's (2012) Weighted Ljung-Box statistics reveal no remaining correlation structure in levels and volatility.

Figure 3. Volatilities in black lines and absolute returns in grey



For each time series, the estimated volatility and the absolute returns are shown in Figure 3. Here we can see that the estimated volatilities are capable of reproducing the variability of returns. Furthermore, the volatility of Southern and its principal product, Copper, evolve in very similar ways. In addition, Volcan is more volatile than the other two mining companies and exhibits an estimated volatility which mimics the IGBVL volatility.

Table 4. Descriptive statistics of volatilities

	Mean	Std Dev	Skewness	Kurtosis	Min	Max
Buenaventura	5.961	1.436	3.6	24.24	4.63	19.48
Southern	6.113	1.967	2.6	11.93	3.9	16.67
Volcan	6.560	3.104	3.35	17.43	3.85	27.12
IGBVL	3.561	1.685	3.85	24.34	2.13	17.46
Copper	3.953	1.596	1.82	7.35	1.83	11.76
Gold-Silver	3.524	0.817	2.68	12.16	2.72	8.02
Lead-Zinc	4.462	1.452	0.15	2.47	1.83	8.01

Table 5. Correlations between volatilities

	Southern	Volcan	IGBVL	Copper	Gold-Siver	Lead-Zinc
Buenaventura	0.58	0.46	0.49	0.41	0.40	0.31
Southern		0.58	0.61	0.84	0.38	0.69
Volcan			0.85	0.47	0.35	0.45
IGBVL				0.54	0.43	0.47
Copper					0.41	0.76
Gold-Silver						0.37

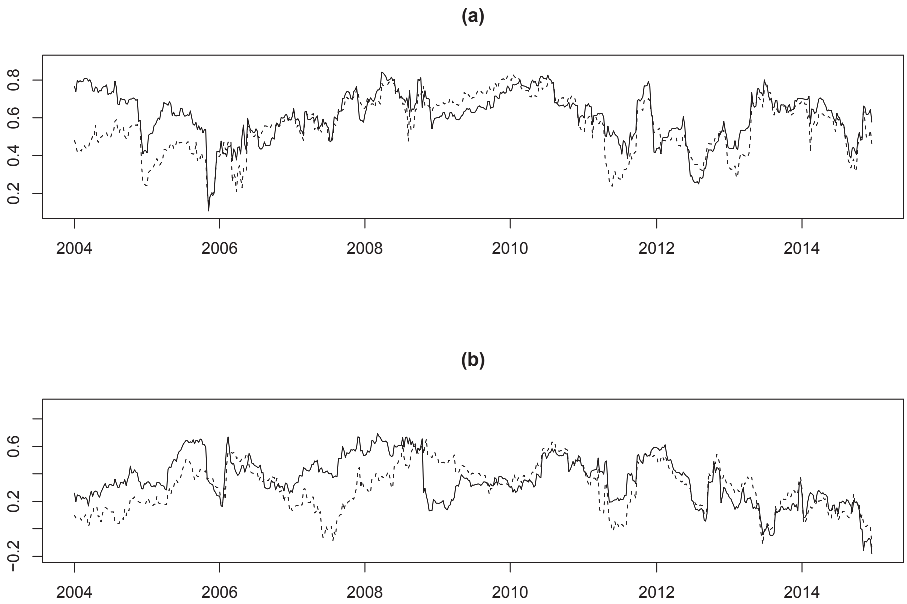
In Table 4 we present some descriptive measures for the estimated volatilities. From the mean values we conclude that the stocks exhibit more mean volatility than the metals. The standard deviation indicates that Volcan and Southern present the highest values, and Gold-Silver the lowest. The variability of the volatility is higher for Volcan, Southern and Buenaventura compared to the precious metal basket.

To measure the strength of the linkages between the volatilities, we calculate the Pearson correlation between volatilities as in Cappiello et al (2006)[5]. These values, consigned in Table 5, show that there are important linkages between the volatilities of the considered time series. Among them, very strong linkages can be noted between the volatilities of Southern with Copper; Copper with Lead-Zinc; and Volcan with IGBVL.

In Figure 4, we show the conditional correlation estimates using the EWMA method for two mining stocks. In (a) we show the correlations between Buenaventura and Gold and Buenaventura and Silver. Notably, since the end of 2005 both correlation time series present almost the same values. The same occurs in (b) when comparing the correlations between Volcan and Lead with Volcan and Zinc, especially starting from 2009. These facts underline the pertinence of working with the Gold-Silver and Lead-Zinc baskets instead of the individual metals.

5 We used σ_t instead of σ_t^2.

Figure 4. Estimated conditional correlation by EWMA. (a) Buenaventura vs Gold (line) and Buenaventura vs Silver (dash). (b) Volcan and Zinc (line) and Volcan vs Lead (dash).



The main aim of this paper is to estimate the linkages between metals and Peruvian mining stocks. Therefore, for each mining company we select the primary production metals and then model some of these together with the IGBVL. Specifically, we estimate the linkages in the following cases: Southern, and Copper; Buenaventura, and Gold-Silver; Volcan, and Lead-Zinc; Volcan, and Silver; IGBVL, and Gold-Silver; and IGBVL, and Copper. In addition, to gain insight into the relationship between the selected Peruvian mining stocks, we considered the cases of Buenaventura and Southern, Buenaventura and Volcan, and Southern and Volcan.

For each of the considered bivariate time series, the conditional correlation was estimated by the EWMA method using DCC-type models (ADCC, DCC and IDCC). We only fitted bivariate DCC-type models instead of trivariate or high dimensional models because we have small-sized time series and DCC-type models impose the same evolution for the bivariate conditional correlation, and assuming that this can be restrictive to explain the dynamics.

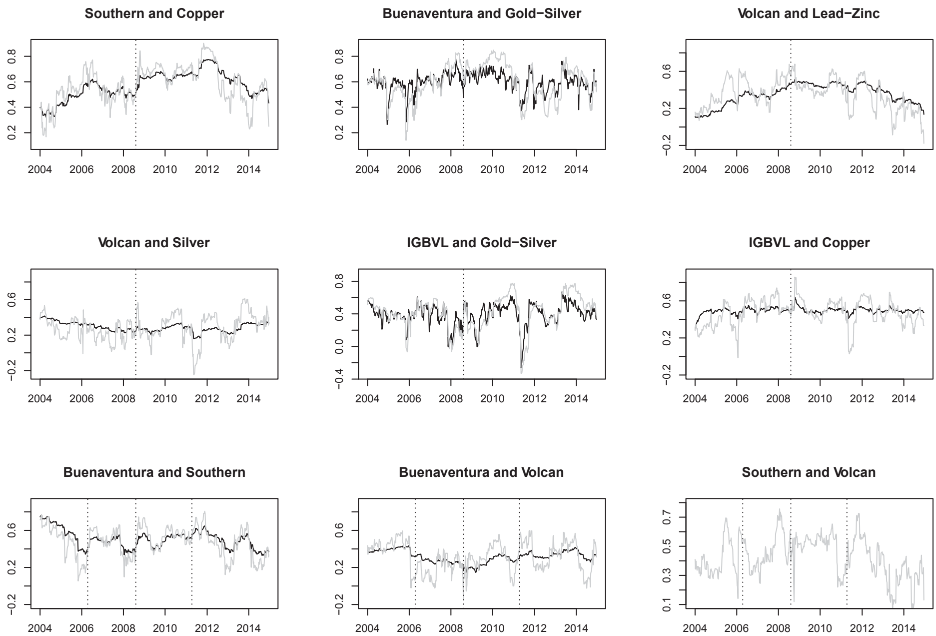
Table 6. Conditional Correlation Model fits

Time series	Model	λ	a	b	H	$H2$
Southern, Copper	IDCC	0.9831			0.23	0.00
		(0.0075)			0.19	0.00
Buenaventura, Gold-Silver	DCC		0.0672	0.7975	0.56	0.13
			(0.0281)	(0.0970)	0.64	0.69
Volcan, Lead-Zinc	IDCC	0.9865			0.18	0.16
		(0.0050)			0.25	0.46
Volcan, Silver	IDCC	0.9896			0.49	0.56
		(0.0071)			0.24	0.97
IGBVL, Gold-Silver	DCC		0.0731	0.8459	0.70	0.99
			(0.0348)	(0.1156)	0.08	0.17
IGBVL, Copper	DCC		0.0150	0.8622	0.58	0.10
			(0.0177)	(0.0986)	0.23	0.51
Buenaventura, Southern	IDCC	0.9803			0.22	0.39
		(0.0062)			0.49	0.12
Buenaventura, Volcan	IDCC	0.9892			0.94	0.47
		(0.0067)			0.85	0.47
Southern, Volcan	DCC		0.0031	0.8934	0.04	0.04
			(0.0236)	(0.4812)	0.07	0.26

[a] Estimates of DCC and IDCC models with standard errors in parenthesis. In columns H and H2 the p-values of Hosking's (1980) multivariate white noise test are presented, where the first and second entries correspond to 5 and 15 lags, respectively. H refers to the residuals (17) and H2 refers to the squared residuals.

In Table 6 we present the parameter estimates of the best DCC-type fits in terms of significance of coefficients, and diagnostics or information criteria. For the IDCC models all λ estimates are highly significant. For the DCC models the estimates of a and b are significant at 5% (using a one-sided alternative hypothesis) except for the estimate of a for the Southern-Volcan case, which is not significant at any reasonable level. Since the $a + b$ and λ estimated values are very close to one, time-varying correlations exibit high persistence. Furthermore, in all fits the p-values of the multivariate Hosking (1980) test for the residuals (16) and its squares indicate no remaining correlation, except for the squares in the Southern-Copper case and for the levels in the Southern-Volcan case. Given the poor results obtained in the Southern-Volcan DCC fit, we do not consider it in the subsequent discussion.

Figure 5. Time-varying correlations; EWMA conditional correlations in grey and (I) DCC correlations in black. The vertical dashed lines correspond to April 2006, August 2008 and April 2011.



In Figure 5 we show the estimated conditional correlations using the DCC-type models (in black) and the EWMA method (in grey). As expected, we observe a time-varying behavior for conditional correlations. In general, the DCC-type conditional correlations are smoothed estimates of the EWMA, which looks more volatile.

From Figure 5 the following can be observed. First, in the case of stocks and the index vs. metals, we observe that the estimated correlations between Southern vs. Copper and Buenaventura vs. Gold-Silver show relatively high values. Similar in size to a lesser extent are those of IGBVL vs. Copper and IGBVL vs. Gold-Silver. Furthermore, Volcan vs. Silver and Volcan vs. Lead-Zinc show smaller relative values for many periods.

In the case of Southern vs. Copper, a considerable increase in correlations is observed after the bankruptcy of Lehman Brothers, which is then followed by a decrease in 2012. A possible hypothesis to explain the increase is the financial crisis of 2008, which would also explain the subsequent decrease once the economy started to improve. In the case of Buenaventura vs. Gold-Silver we can distinguish two periods of different correlations levels. The first one up to the 2011 with high values and low volatility, and a second period starting in 2012 with lower values but higher volatility. This, as stated earlier, could be hypothesized due to the trend of using gold and silver as safe havens during financial crises.

In the case of Volcan vs. Lead-Zinc, we can distinguish two different trends: one of increasing correlations up to 2010, and then another of decrease back to the levels seen at the start of the observed period. In the case of Volcan vs. Silver, correlations fluctuate around a somewhat constant value. In both cases, observed correlation values are consistently low for the entire observed period.

In the case of IGBVL and Gold-Silver, considerable variability in the estimated correlations is observed, with steep rises during the second half of 2008 and 2011. The same is true of the correlation values estimated using EWMA for IGBVL vs. Copper.

When analyzing the time-varying correlations between pairs of mining companies, we note that given the behavior of EWMA estimated values the correlations between stocks have had periods of ups and downs but at different levels, and according to the DCC-type estimates, overall, the correlation between Buenaventura and Southern are bigger than that between Buenaventura and Volcan.

Based on our findings, we are of the opinion that further research could help to understand the effect of some (historical) events on the correlations. In the period considered in this paper we can identify at least three major events that appear to affect the correlations: the *Global Crisis,* which started around the time of the Lehman-Brothers bankruptcy in August 2008, and the 2006 and 2011 presidential elections in Peru. Based on the scope of the influence of these events, we consider the impact of the Global Crisis in all the considered cases, and the impact of the presidential election in the case of bivariate mining stocks only. Specifically, we are interested in the increase in correlation associated with these events. The increase in correlation can occur immediately after the event or after a short delay. In Figure 5 we show vertical lines corresponding to August 2008 (the start of the Global Crisis), and April of both 2006 and 2011 (first round of the respective presidential elections). As can be observed in Figure 5, the election of 2011 seems to increase the correlation in the three mining stock cases considered, for Buenaventura vs. Southern, Buenaventura vs. Volcan, and Southern vs Volcan. However, in the election of 2006 an increase in correlation is only noted for the Buenaventura vs. Southern case. As regards the impact of Lehman-Brothers bankruptcy, an increase of correlations is detected for all the considered cases except for Volcan vs. Silver and Southern vs. Volcan.

4. CONCLUSIONS

The main objective of this study was to examine the comovements between metal and mining stock returns in Peru's BVL, as well as the comovements between metal and its principal stock market index. Multivariate GARCH models with time-varying correlations and the EWMA method were estimated to capture a broad range of possible relationships.

We found evidence of five important aspects. First, weekly return volatilities of Peruvian mining stocks are sensitive to both past shocks and volatility. This means that both shocks and volatilities are not completely absorbed at the time they occur, but instead tend to have a long-lasting effect on future mining stock returns and volatilities that usually take some time to dissipate.

Second, we found that the volatility of the principal mining stocks mimics the behavior of metal volatilities.

Third, we confirm the pertinence of using metal baskets like Gold-Silver and Lead-Zinc to capture the conditional correlations for Buenaventura with Gold and Silver, and Volcan with Lead and Zinc, respectively. In a similar fashion, we also confirm the pertinence of using weekly data to capture long-term trends, as weekly data mitigates the problem of a lack of synchronicity due to holidays, and also allows us to obtain a much smoother estimate of correlation than with daily returns.

Fourth, we observe important correlations in the case of stocks and indexes vs. metals, with some of them showing relatively high values as in the case of Southern vs. Copper, and Buenaventura vs. Gold-Silver. In additional, for some of these correlations we observe a considerable increase in values after certain events, such as, for example, the Lehman Brothers bankruptcy.

Fifth, when analyzing the linkages in each pair of the mining stocks we found important time-varying correlations that exhibit ups and downs. Moreover, the analysis of the correlation among mining stocks indicates that the presidential election of 2011 appears to increase the correlation in the three mining stock cases considered: Buenaventura vs. Southern, Buenaventura vs. Volcan, and Southern vs Volcan. However, in the election of 2006, we only note the increase in correlation for the Buenaventura vs. Southern case.

Finally, in this paper we have studied the linkages between metal returns and Peruvian mining stocks and the index. The results of this study constitute an exploratory analysis, where patterns and shifts in long-term relationships have been identified. As far as we known, this is the first study on the estimation of comovements between metal returns and Peruvian mining stocks and the index. Therefore, we believe these results can be used for further research, with hypotheses that seek to explain the movements in these relationships. The likelihood of such hypotheses warrants further study on the economic fundamentals behind them.

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